Try 36 medium

May 6, 2025

[ ]:
```python
import os
import random
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras import backend as K
from tensorflow.keras import layers, Model
from tensorflow.keras.utils import plot_model
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve, auc, accuracy_score
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau,␣
↪ModelCheckpoint
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'

# Seeds
random.seed(42)
np.random.seed(42)
tf.random.set_seed(42)

# Configuration
IMG_SIZE = (128, 128)
BATCH_SIZE = 32
EPOCHS = 150
DATA_PATH = "/kaggle/input/socofing/SOCOFing/Real/"
ALTER_MEDIUM_PATH = "/kaggle/input/socofing/SOCOFing/Altered/Altered-Medium/"

# Data Loading and Preprocessing
def load_fingerprint_data(data_path):
    images = []
    labels = []

    for filename in os.listdir(data_path):
        if filename.endswith(".BMP"):
            parts = filename.split('__')
            person_id = parts[0]
            finger_info = parts[1].split('_')
```

```
            hand = finger_info[1]
            finger_type = finger_info[2]
            label = f"{person_id}_{hand}_{finger_type}"

            img_path = os.path.join(data_path, filename)
            img = load_img(img_path, color_mode='grayscale',␣
↪target_size=IMG_SIZE)
            img = img_to_array(img).astype('float32') / 255.0
            images.append(img)
            labels.append(label)

    images = np.array(images)
    labels = np.array(labels)

    if images.ndim != 4:
        raise ValueError(f"Expected 4D array (num_samples, height, width,␣
↪channels), got {images.shape}")

    return images, labels

# Load both datasets
images_real, labels_real = load_fingerprint_data(DATA_PATH)
images_alter_medium, labels_alter_medium =␣
↪load_fingerprint_data(ALTER_MEDIUM_PATH)
print(f"Loaded {len(images_real)} images from Real dataset")
print(f"Loaded {len(images_alter_medium)} images from Alter-medium dataset")
print(f"Image shape: {images_real[0].shape}")

# Pair Generation
def create_pairs(images_real, labels_real, images_alter_medium,␣
↪labels_alter_medium):
    label_to_real_image = {}
    for img, label in zip(images_real, labels_real):
        label_to_real_image[label] = img

    label_to_alter_images = {}
    for img, label in zip(images_alter_medium, labels_alter_medium):
        if label not in label_to_alter_images:
            label_to_alter_images[label] = []
        label_to_alter_images[label].append(img)

    # Generate positive pairs
    positive_pairs = []
    for label in label_to_real_image:
        if label in label_to_alter_images:
            real_img = label_to_real_image[label]
            for alter_img in label_to_alter_images[label]:
```

```
                positive_pairs.append([real_img, alter_img])

    # Generate negative pairs
    negative_pairs = []
    num_positive = len(positive_pairs)

    common_labels = list(set(label_to_real_image.keys()) &␣
 ↪set(label_to_alter_images.keys()))

    while len(negative_pairs) < num_positive:
        label1 = random.choice(common_labels)
        label2 = random.choice(common_labels)
        if label1 != label2:
            real_img = label_to_real_image[label1]
            alter_img = random.choice(label_to_alter_images[label2])
            negative_pairs.append([real_img, alter_img])

    # Combine and shuffle pairs
    pairs = positive_pairs + negative_pairs
    pair_labels = [1] * len(positive_pairs) + [0] * len(negative_pairs)

    indices = np.arange(len(pairs))
    np.random.shuffle(indices)
    pairs = np.array(pairs)[indices]
    pair_labels = np.array(pair_labels)[indices]

    return pairs, pair_labels

pairs, labels = create_pairs(images_real, labels_real, images_alter_medium,␣
 ↪labels_alter_medium)
print(f"Generated {len(pairs)} pairs")

# Train/Validation/Test Split
X_train, X_temp, y_train, y_temp = train_test_split(
    pairs, labels, train_size=0.7, test_size=0.3, random_state=42,␣
 ↪stratify=labels
)

X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, train_size=0.5, test_size=0.5, random_state=42,␣
 ↪stratify=y_temp
)

print(f"Training pairs: {len(X_train)}")
print(f"Validation pairs: {len(X_val)}")
print(f"Test pairs: {len(X_test)}")
print(f"Training class distribution: {np.bincount(y_train)}")
```

```
print(f"Validation class distribution: {np.bincount(y_val)}")
print(f"Test class distribution: {np.bincount(y_test)}")
```

```
2025-05-05 22:28:32.457492: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:477] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
E0000 00:00:1746484112.480114     333 cuda_dnn.cc:8310] Unable to register cuDNN
factory: Attempting to register factory for plugin cuDNN when one has already
been registered
E0000 00:00:1746484112.486912     333 cuda_blas.cc:1418] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
```

```
Loaded 6000 images from Real dataset
Loaded 17067 images from Alter-Easy dataset
Image shape: (128, 128, 1)
```

```
I0000 00:00:1746484159.927606     333 gpu_device.cc:2022] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 15513 MB memory:  -> device:
0, name: Tesla P100-PCIE-16GB, pci bus id: 0000:00:04.0, compute capability: 6.0
```

```
Generated 34134 pairs
Training pairs: 23893
Validation pairs: 5120
Test pairs: 5121
Training class distribution: [11946 11947]
Validation class distribution: [2560 2560]
Test class distribution: [2561 2560]
```

[2]:
```
# Siamese Network Architecture
def create_embedding_network(input_shape):
    inputs = layers.Input(shape=input_shape)
    x = layers.Conv2D(32, (5, 5), activation='relu', kernel_regularizer=tf.
↪keras.regularizers.l2(0.01))(inputs)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)

    x = layers.Conv2D(64, (3, 3), activation='relu', kernel_regularizer=tf.
↪keras.regularizers.l2(0.01))(x)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)

    x = layers.Conv2D(128, (3, 3), activation='relu', kernel_regularizer=tf.
↪keras.regularizers.l2(0.01))(x)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)
```

```
    x = layers.Conv2D(256, (3, 3), activation='relu', kernel_regularizer=tf.
 ↪keras.regularizers.l2(0.01))(x)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)

    x = layers.Conv2D(512, (3, 3), activation='relu', kernel_regularizer=tf.
 ↪keras.regularizers.l2(0.01))(x)
    x = layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = layers.BatchNormalization()(x)

    x = layers.GlobalAveragePooling2D()(x)
    x = layers.Dense(256, activation='relu', kernel_regularizer=tf.keras.
 ↪regularizers.l2(0.01))(x)
    x = layers.Dropout(0.35)(x)
    x = layers.Dense(256, activation=None)(x)

    return Model(inputs, x)

def build_siamese_model(input_shape):
    input_a = layers.Input(shape=input_shape)
    input_b = layers.Input(shape=input_shape)

    embedding_network = create_embedding_network(input_shape)

    embedding_a = embedding_network(input_a)
    embedding_b = embedding_network(input_b)

    distance = layers.Lambda(
        lambda embeddings: tf.abs(embeddings[0] - embeddings[1])
    )([embedding_a, embedding_b])

    output = layers.Dense(1, activation='sigmoid')(distance)

    return Model(inputs=[input_a, input_b], outputs=output)

input_shape = IMG_SIZE + (1,)
siamese_model = build_siamese_model(input_shape)
siamese_model.summary()

# Compile the model
siamese_model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])

# Training
early_stopping = EarlyStopping(monitor='val_loss', patience=10,␣
 ↪restore_best_weights=True)
```

```
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=5,␣
↪min_lr=1e-6)
checkpoint = ModelCheckpoint('best_model.keras', monitor='val_loss',␣
↪save_best_only=True)
```

```
Model: "functional_1"


 Layer (type)                Output Shape                     Param #  Connected␣
↪to

 input_layer (InputLayer)    (None, 128, 128, 1)                    0  -         ␣
↪

 input_layer_1               (None, 128, 128, 1)                    0  -         ␣
↪
 (InputLayer)                                                                   ␣
↪

 functional (Functional)     (None, 256)                    1,769,600 ␣
↪input_layer[0][0],
                                                                      ␣
↪input_layer_1[0][0]

 lambda (Lambda)             (None, 256)                            0 ␣
↪functional[0][0],
                                                                      ␣
↪functional[1][0]

 dense_2 (Dense)             (None, 1)                            257 ␣
↪lambda[0][0]


 Total params: 1,769,857 (6.75 MB)

 Trainable params: 1,767,873 (6.74 MB)

 Non-trainable params: 1,984 (7.75 KB)
```

[3]:
```
history = siamese_model.fit(
    [X_train[:, 0], X_train[:, 1]],
    y_train,
    validation_data=([X_val[:, 0], X_val[:, 1]], y_val),
    batch_size=BATCH_SIZE,
```

```
    epochs=EPOCHS,
    callbacks=[early_stopping, reduce_lr, checkpoint]
)

K.clear_session()
tf.compat.v1.reset_default_graph()

# Training Curves
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.savefig('/kaggle/working/training_curves.png')
plt.show()

# Model Evaluation
def evaluate_model(model, X, y, set_name=''):
    batch_size = 8
    y_pred = []
    for i in range(0, len(X), batch_size):
        batch_X = X[i:i + batch_size]
        batch_pred = model.predict([batch_X[:, 0], batch_X[:, 1]],␣
↪batch_size=batch_size, verbose=0)
        y_pred.extend(batch_pred)
    y_pred = np.array(y_pred)
    fpr, tpr, thresholds = roc_curve(y, y_pred)
    roc_auc = auc(fpr, tpr)

    plt.figure()
    plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area =␣
↪{roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
```

```python
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'Receiver Operating Characteristic ({set_name})')
    plt.legend(loc="lower right")
    plt.savefig(f'/kaggle/working/roc_curve_{set_name.lower()}.png')
    plt.show()

    return roc_auc

print("Training Evaluation:")
train_auc = evaluate_model(siamese_model, X_train, y_train, 'Training')

print("\nValidation Evaluation:")
val_auc = evaluate_model(siamese_model, X_val, y_val, 'Validation')

print("\nTest Evaluation:")
test_auc = evaluate_model(siamese_model, X_test, y_test, 'Test')

train_acc = history.history['accuracy'][-1]
val_acc = history.history['val_accuracy'][-1]
test_acc = siamese_model.evaluate([X_test[:, 0], X_test[:, 1]], y_test)[1]

print(f"\nFinal Metrics:")
print(f"Training Accuracy: {train_acc:.4f} | AUC: {train_auc:.4f}")
print(f"Validation Accuracy: {val_acc:.4f} | AUC: {val_auc:.4f}")
print(f"Test Accuracy: {test_acc:.4f} | AUC: {test_auc:.4f}")

# Real Photo Evaluation
def visualize_predictions(model, X, y, num_samples=5):
    indices = np.random.choice(len(X), num_samples)
    sample_pairs = X[indices]
    sample_labels = y[indices]

    predictions = model.predict([sample_pairs[:, 0], sample_pairs[:, 1]])

    plt.figure(figsize=(15, 5))
    for i in range(num_samples):
        plt.subplot(2, num_samples, i+1)
        plt.imshow(sample_pairs[i][0].squeeze(), cmap='gray')
        plt.title(f"Label: {sample_labels[i]}\nPred: {predictions[i][0]:.2f}")
        plt.axis('off')

        plt.subplot(2, num_samples, i+1+num_samples)
        plt.imshow(sample_pairs[i][1].squeeze(), cmap='gray')
        plt.axis('off')

    plt.tight_layout()
```

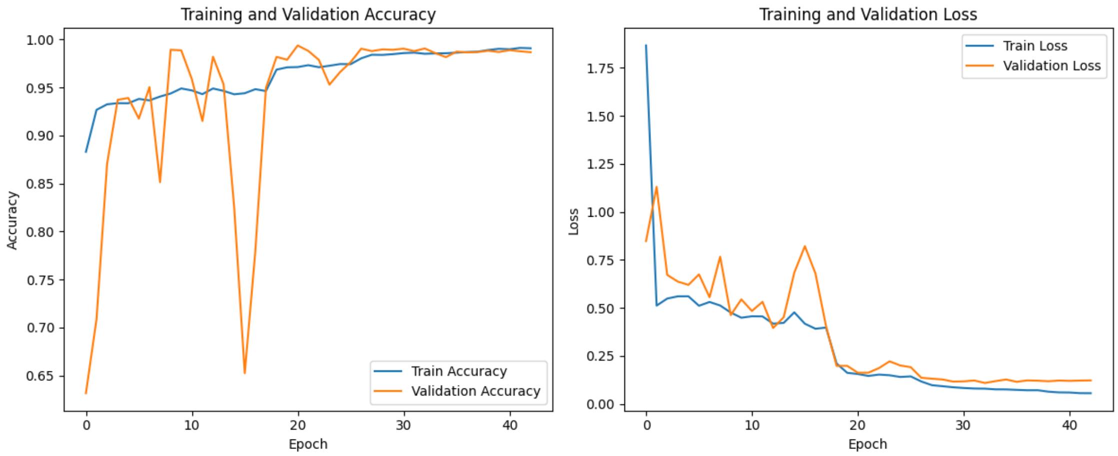
```
    plt.show()

print("Sample Test Predictions:")
visualize_predictions(siamese_model, X_test, y_test)
```

```
Epoch 1/150

WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
I0000 00:00:1746484180.169779     364 service.cc:148] XLA service 0x7f0fdc002e40
initialized for platform CUDA (this does not guarantee that XLA will be used).
Devices:
I0000 00:00:1746484180.170162     364 service.cc:156]   StreamExecutor device
(0): Tesla P100-PCIE-16GB, Compute Capability 6.0
I0000 00:00:1746484180.898478     364 cuda_dnn.cc:529] Loaded cuDNN version
90300

  7/747            16s 22ms/step - accuracy:
0.4594 - loss: 10.8021

I0000 00:00:1746484186.548504     364 device_compiler.h:188] Compiled cluster
using XLA!  This line is logged at most once for the lifetime of the process.

747/747            39s 34ms/step -
accuracy: 0.8282 - loss: 4.1412 - val_accuracy: 0.6314 - val_loss: 0.8483 -
learning_rate: 0.0010
Epoch 2/150
747/747            16s 22ms/step -
accuracy: 0.9257 - loss: 0.5129 - val_accuracy: 0.7086 - val_loss: 1.1309 -
learning_rate: 0.0010
Epoch 3/150
747/747            16s 22ms/step -
accuracy: 0.9347 - loss: 0.5483 - val_accuracy: 0.8707 - val_loss: 0.6721 -
learning_rate: 0.0010
Epoch 4/150
747/747            16s 22ms/step -
accuracy: 0.9264 - loss: 0.6268 - val_accuracy: 0.9371 - val_loss: 0.6373 -
learning_rate: 0.0010
Epoch 5/150
747/747            16s 22ms/step -
accuracy: 0.9358 - loss: 0.5370 - val_accuracy: 0.9391 - val_loss: 0.6201 -
learning_rate: 0.0010
Epoch 6/150
747/747            16s 22ms/step -
accuracy: 0.9360 - loss: 0.5202 - val_accuracy: 0.9176 - val_loss: 0.6746 -
learning_rate: 0.0010
Epoch 7/150
747/747            16s 22ms/step -
accuracy: 0.9331 - loss: 0.5393 - val_accuracy: 0.9504 - val_loss: 0.5559 -
learning_rate: 0.0010
```

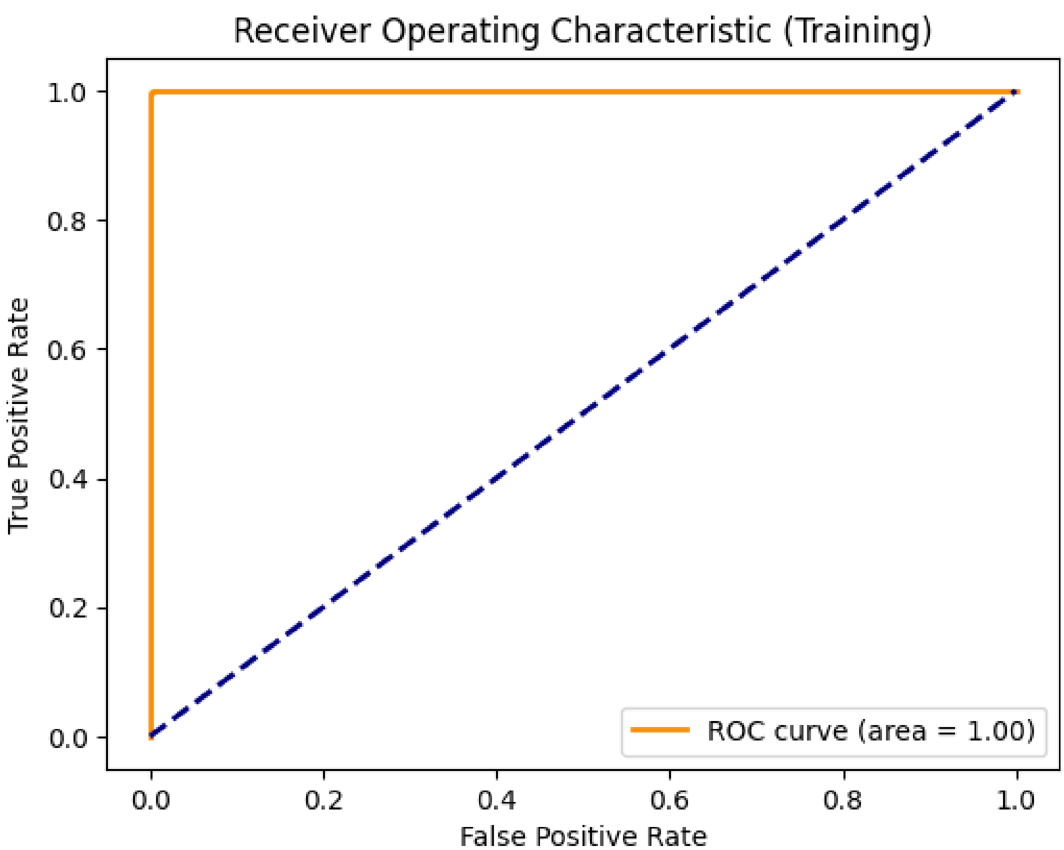
```
Epoch 8/150
747/747              16s 22ms/step -
accuracy: 0.9413 - loss: 0.5037 - val_accuracy: 0.8514 - val_loss: 0.7669 -
learning_rate: 0.0010
Epoch 9/150
747/747              16s 22ms/step -
accuracy: 0.9440 - loss: 0.4797 - val_accuracy: 0.9893 - val_loss: 0.4628 -
learning_rate: 0.0010
Epoch 10/150
747/747              16s 22ms/step -
accuracy: 0.9509 - loss: 0.4338 - val_accuracy: 0.9887 - val_loss: 0.5448 -
learning_rate: 0.0010
Epoch 11/150
747/747              16s 22ms/step -
accuracy: 0.9466 - loss: 0.4784 - val_accuracy: 0.9588 - val_loss: 0.4844 -
learning_rate: 0.0010
Epoch 12/150
747/747              16s 22ms/step -
accuracy: 0.9443 - loss: 0.4485 - val_accuracy: 0.9150 - val_loss: 0.5319 -
learning_rate: 0.0010
Epoch 13/150
747/747              16s 22ms/step -
accuracy: 0.9487 - loss: 0.4164 - val_accuracy: 0.9820 - val_loss: 0.3957 -
learning_rate: 0.0010
Epoch 14/150
747/747              16s 22ms/step -
accuracy: 0.9446 - loss: 0.4304 - val_accuracy: 0.9533 - val_loss: 0.4517 -
learning_rate: 0.0010
Epoch 15/150
747/747              16s 22ms/step -
accuracy: 0.9459 - loss: 0.4511 - val_accuracy: 0.8252 - val_loss: 0.6836 -
learning_rate: 0.0010
Epoch 16/150
747/747              16s 22ms/step -
accuracy: 0.9416 - loss: 0.4187 - val_accuracy: 0.6523 - val_loss: 0.8215 -
learning_rate: 0.0010
Epoch 17/150
747/747              16s 22ms/step -
accuracy: 0.9470 - loss: 0.3908 - val_accuracy: 0.7797 - val_loss: 0.6796 -
learning_rate: 0.0010
Epoch 18/150
747/747              16s 22ms/step -
accuracy: 0.9432 - loss: 0.4200 - val_accuracy: 0.9494 - val_loss: 0.4049 -
learning_rate: 0.0010
Epoch 19/150
747/747              16s 22ms/step -
accuracy: 0.9649 - loss: 0.2546 - val_accuracy: 0.9818 - val_loss: 0.1987 -
learning_rate: 2.0000e-04
```

```
Epoch 20/150
747/747              16s 22ms/step -
accuracy: 0.9724 - loss: 0.1653 - val_accuracy: 0.9789 - val_loss: 0.1987 -
learning_rate: 2.0000e-04
Epoch 21/150
747/747              16s 22ms/step -
accuracy: 0.9724 - loss: 0.1534 - val_accuracy: 0.9937 - val_loss: 0.1629 -
learning_rate: 2.0000e-04
Epoch 22/150
747/747              16s 22ms/step -
accuracy: 0.9742 - loss: 0.1451 - val_accuracy: 0.9881 - val_loss: 0.1632 -
learning_rate: 2.0000e-04
Epoch 23/150
747/747              16s 22ms/step -
accuracy: 0.9714 - loss: 0.1489 - val_accuracy: 0.9787 - val_loss: 0.1871 -
learning_rate: 2.0000e-04
Epoch 24/150
747/747              16s 22ms/step -
accuracy: 0.9702 - loss: 0.1575 - val_accuracy: 0.9529 - val_loss: 0.2221 -
learning_rate: 2.0000e-04
Epoch 25/150
747/747              16s 22ms/step -
accuracy: 0.9743 - loss: 0.1428 - val_accuracy: 0.9660 - val_loss: 0.2008 -
learning_rate: 2.0000e-04
Epoch 26/150
747/747              16s 22ms/step -
accuracy: 0.9752 - loss: 0.1441 - val_accuracy: 0.9764 - val_loss: 0.1918 -
learning_rate: 2.0000e-04
Epoch 27/150
747/747              16s 22ms/step -
accuracy: 0.9772 - loss: 0.1265 - val_accuracy: 0.9904 - val_loss: 0.1365 -
learning_rate: 4.0000e-05
Epoch 28/150
747/747              16s 22ms/step -
accuracy: 0.9838 - loss: 0.1008 - val_accuracy: 0.9879 - val_loss: 0.1318 -
learning_rate: 4.0000e-05
Epoch 29/150
747/747              16s 22ms/step -
accuracy: 0.9839 - loss: 0.0944 - val_accuracy: 0.9896 - val_loss: 0.1278 -
learning_rate: 4.0000e-05
Epoch 30/150
747/747              16s 22ms/step -
accuracy: 0.9840 - loss: 0.0892 - val_accuracy: 0.9893 - val_loss: 0.1168 -
learning_rate: 4.0000e-05
Epoch 31/150
747/747              16s 22ms/step -
accuracy: 0.9856 - loss: 0.0855 - val_accuracy: 0.9904 - val_loss: 0.1180 -
learning_rate: 4.0000e-05
```

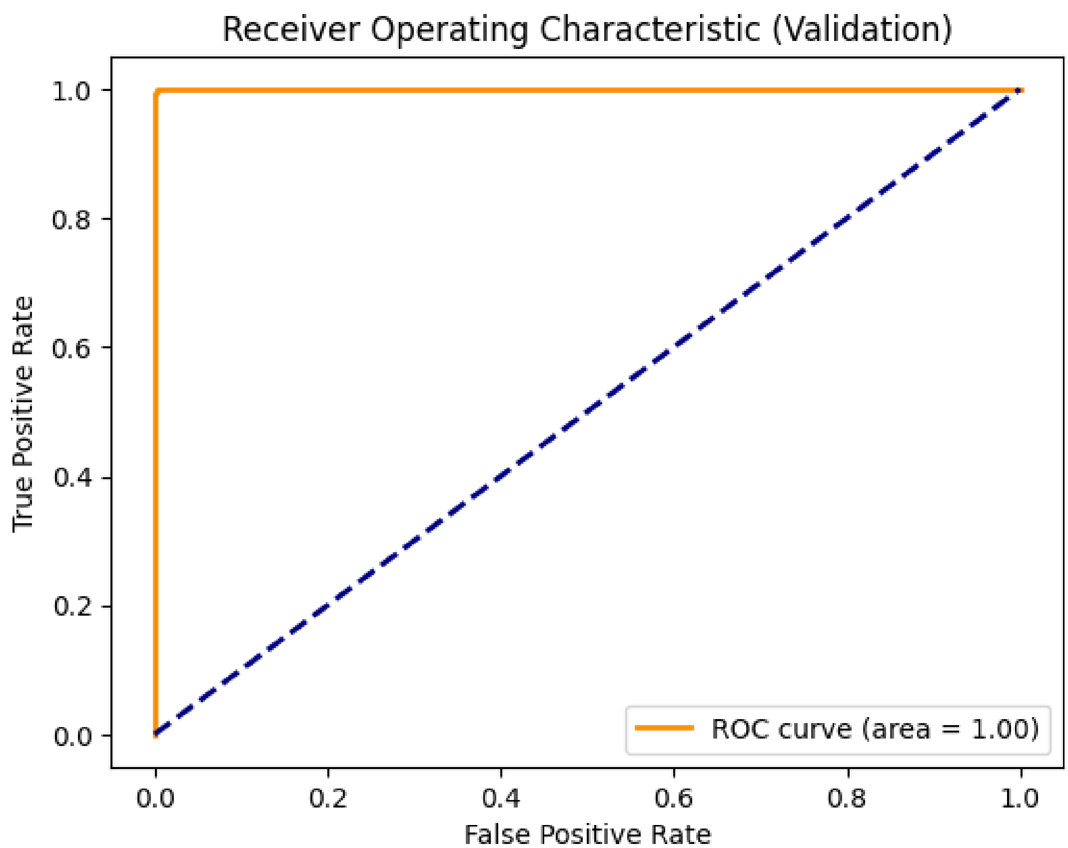
```
Epoch 32/150
747/747            16s 22ms/step -
accuracy: 0.9860 - loss: 0.0812 - val_accuracy: 0.9879 - val_loss: 0.1224 -
learning_rate: 4.0000e-05
Epoch 33/150
747/747            16s 22ms/step -
accuracy: 0.9848 - loss: 0.0825 - val_accuracy: 0.9906 - val_loss: 0.1096 -
learning_rate: 4.0000e-05
Epoch 34/150
747/747            16s 22ms/step -
accuracy: 0.9863 - loss: 0.0762 - val_accuracy: 0.9857 - val_loss: 0.1191 -
learning_rate: 4.0000e-05
Epoch 35/150
747/747            16s 22ms/step -
accuracy: 0.9863 - loss: 0.0742 - val_accuracy: 0.9816 - val_loss: 0.1276 -
learning_rate: 4.0000e-05
Epoch 36/150
747/747            16s 22ms/step -
accuracy: 0.9873 - loss: 0.0726 - val_accuracy: 0.9873 - val_loss: 0.1157 -
learning_rate: 4.0000e-05
Epoch 37/150
747/747            16s 22ms/step -
accuracy: 0.9860 - loss: 0.0724 - val_accuracy: 0.9865 - val_loss: 0.1229 -
learning_rate: 4.0000e-05
Epoch 38/150
747/747            16s 22ms/step -
accuracy: 0.9873 - loss: 0.0720 - val_accuracy: 0.9869 - val_loss: 0.1214 -
learning_rate: 4.0000e-05
Epoch 39/150
747/747            16s 22ms/step -
accuracy: 0.9891 - loss: 0.0645 - val_accuracy: 0.9883 - val_loss: 0.1185 -
learning_rate: 8.0000e-06
Epoch 40/150
747/747            16s 22ms/step -
accuracy: 0.9892 - loss: 0.0616 - val_accuracy: 0.9869 - val_loss: 0.1222 -
learning_rate: 8.0000e-06
Epoch 41/150
747/747            16s 22ms/step -
accuracy: 0.9888 - loss: 0.0614 - val_accuracy: 0.9889 - val_loss: 0.1206 -
learning_rate: 8.0000e-06
Epoch 42/150
747/747            16s 22ms/step -
accuracy: 0.9905 - loss: 0.0578 - val_accuracy: 0.9877 - val_loss: 0.1221 -
learning_rate: 8.0000e-06
Epoch 43/150
747/747            16s 22ms/step -
accuracy: 0.9914 - loss: 0.0559 - val_accuracy: 0.9867 - val_loss: 0.1229 -
learning_rate: 8.0000e-06
```



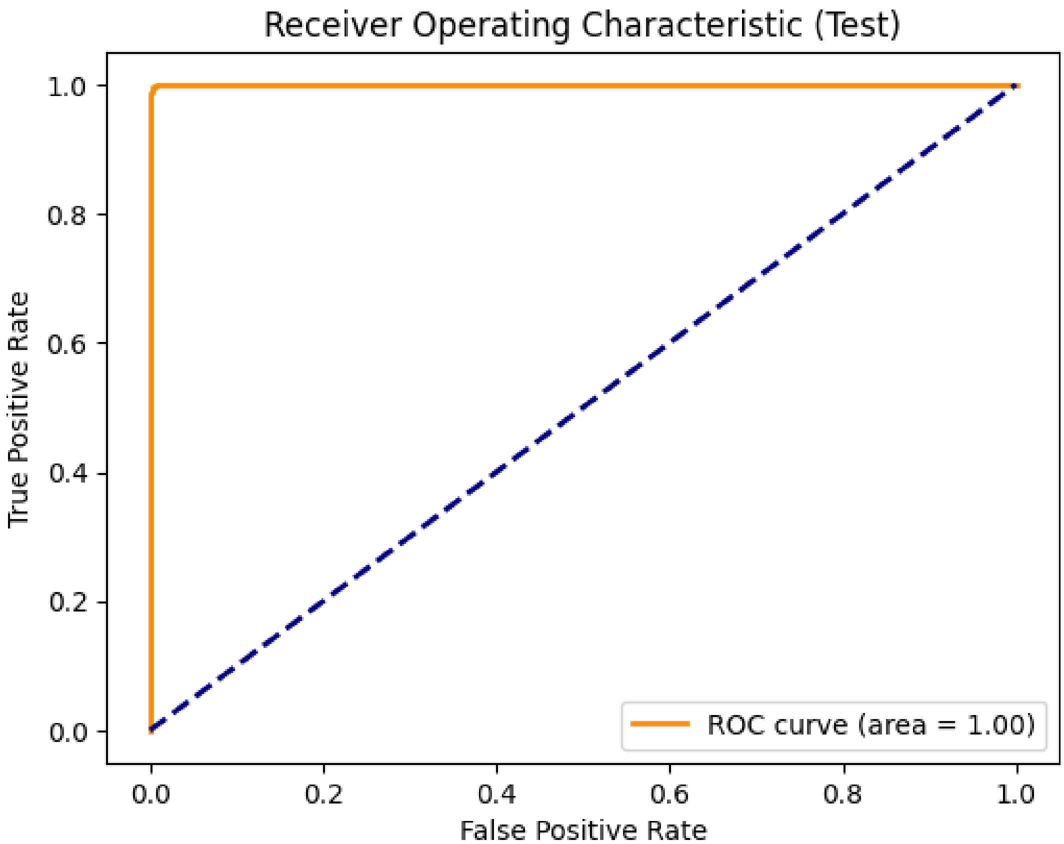
Training Evaluation:



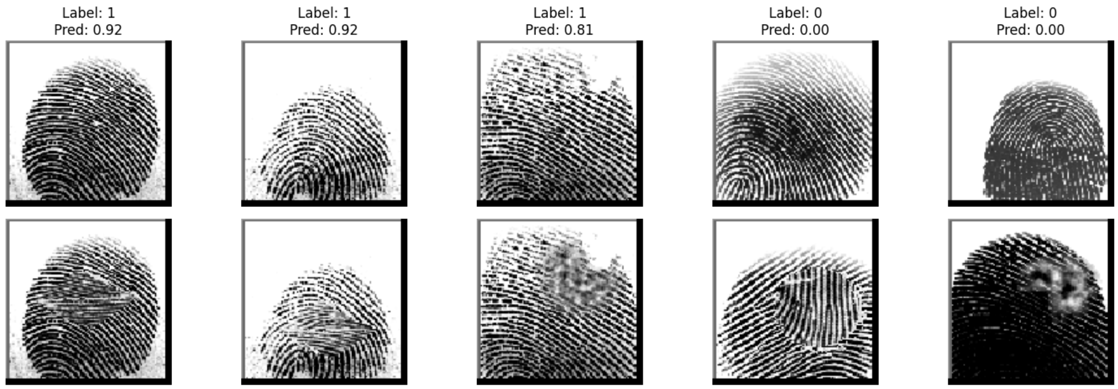
Validation Evaluation:



Test Evaluation:




```
161/161              3s 11ms/step -
accuracy: 0.9914 - loss: 0.1121

Final Metrics:
Training Accuracy: 0.9908 | AUC: 1.0000
Validation Accuracy: 0.9867 | AUC: 0.9999
Test Accuracy: 0.9904 | AUC: 0.9999
Sample Test Predictions:
1/1              0s 20ms/step
```


Label: 1
Pred: 0.92
Label: 1
Pred: 0.92
Label: 1
Pred: 0.81
Label: 0
Pred: 0.00
Label: 0
Pred: 0.00